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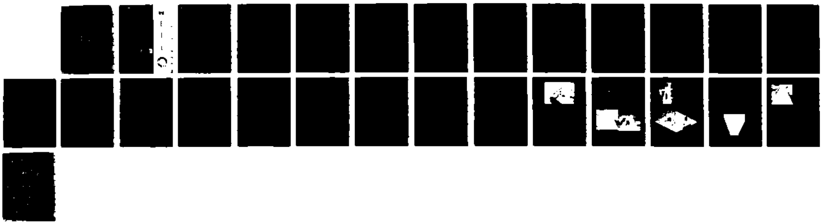

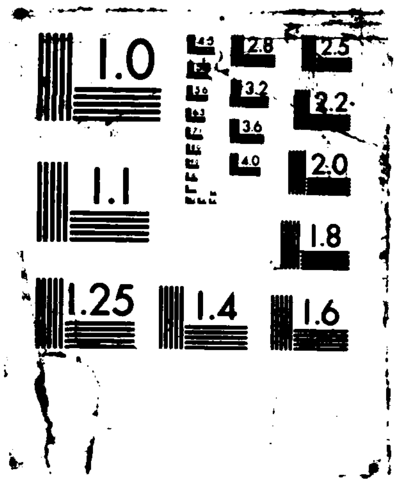
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ETL-0490

Building a 3-D world model for a mobile robot from sensory data

Minoru Asada

Center for Automation Research
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College Park, Maryland 20742

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This paper presents a method for building a 3-D world model for a mobile robot from sensory data. The 3-D world model consists of three kinds of maps: a sensor map, a local map and a global map. A range image (sensor map) is transformed to a height map (local map) with respect to a mobile robot. First, the height map is segmented into four categories (unexplored, occluded, traversable, and obstacle regions) for obstacle detection and path planning. Next, obstacle regions are classified into artificial objects (buildings, cars, road signs, etc.) or natural objects (trees, bushes, etc.) using both the height image and video image. One drawback of the height map--the recovery of vertical planes--is overcome by the utilization of multiple height maps which include the maximum and minimum height of each point, and the number of points in the range image mapped into one point in the height map. The multiple height map is useful not only for finding vertical planes in the height map but also for segmentation of the video image. Finally, the height maps are integrated into a global map by matching geometrical properties and updating region labels. The method is tested on a model including many objects, such as trees, buildings, cars, and so on.

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1. INTRODUCTION

The development of an Autonomous Land Vehicle (ALV) is a central problem in artificial intelligence and robotics, and has been extensively studied [1-12]. To perform visual navigation, a robot must gather information about its environment through external sensors, interpret the output of these sensors, construct a scene map and a plan sufficient for the task at hand, and then monitor and execute the plan.

As a first step, real time visual navigation systems for road following were developed in which simple methods for detecting road edges were applied in simple environments [1,4,5,12, etc.]. For even slightly more complicated scenes, the difficulty of the problem increases dramatically; therefore a world model such as a map could be very important for successful navigation through such environments.

Sometimes, accurate, quantitative maps may be available in advance [13], but more often, maps are less descriptive and provide only global information, as in a conventional geographical map [14]. In other cases, the robot may try to construct the map from sensory data in unknown environments. Elfes [15] developed a sonar-based mapping and navigation system which constructs sonar maps of the environment viewed from the top and updates them with recently acquired sonar information. Tsuji and Zheng [16] discussed the differences between 2-D maps like Elfes's and the perspective maps proposed in their stereo-vision-based mobile robot system. Their point is that 2-D maps are easy to understand but do not naturally capture sensor resolution and accuracy. They

used perspective maps for navigation in which 3-D information obtained by stereo vision is represented in the image coordinate system.

Range images are attractive because direct use of 3-D information is possible from these images. Various methods for acquisition of range images are described in [17]. Two kinds of techniques have been developed for range image processing. One is to apply masks to range images for edge detection [18], as in conventional 2-D intensity image analysis. These methods are suitable for obstacle detection in outdoor scene [19,20] because of fast processing which is necessary for real time navigation. On the other hand, extraction of geometrical properties such as surface normals and curvatures from a range image is also important for segmentation. The common approach involves fitting a surface normal to each pixel [21,22 etc.], then classifying each point according to its geometrical properties.

In this paper, we propose a method for building a 3-D world model for a mobile robot from sensory data derived from outdoor scenes. The 3-D world model consists of three kinds of maps: a sensor map, a local map, and a global map. In our system, a range image (sensor map) is transformed to a height map (local map) with respect to the mobile robot in which gray levels show the height from the assumed ground plane. Segmentation of the height map into unexplored, occluded, traversable and obstacle regions is straightforward from the height information. Moreover, obstacle regions are classified into artificial objects or natural objects according to their geometrical properties such as slope and curvature, which are easily obtained by applying simple mask operators to the height map. A drawback of the height map—recovery of planes vertical to the

ground plane—is overcome by using multiple height maps which include the maximum and minimum height for each point on the ground plane. Multiple height maps are useful not only for finding vertical planes but also for mapping obstacle regions into the video image (one of the sensor maps) for segmentation.

Results obtained using a landscape model and the Maryland ALV simulator [4] are discussed in the next section.

2. SYSTEM CONFIGURATION

2.1 Physical ALV Simulation System

Our physical ALV simulation system was developed in our laboratory [4] to provide a low cost experimental environment for navigation (as compared with a real outdoor vehicle [7,19]). A range finder based on structured light was recently added to this system. Planes of light are projected from a rotating mirror controlled by a stepping motor (see [23] for more detail). More recently, we extended the system in two ways. First, we developed a drive simulator program which controls the speed and steering angle of the vehicle during the motion. The camera height and camera tilt relative to the ground plane are kept constant during the motion through position feedback from three leg sensors attached to the camera (see [24] for more detail).

Previously, a terrain board on which a road network is painted was used. It was oriented vertically to increase the flexibility of the camera motion simulated by the robot arm. Due to the vertical orientation, it was very difficult to put object models such as trees, bushes, buildings, and other vehicles on the board.

We are therefore now using a horizontal terrain board so that we can set up object models without permanently fixing their positions. Figure 1 shows a picture of the new board with many object models such as trees, bushes, cabins, a mail box, and cars. The camera is aimed at the board to input a picture.

2.2 Overview of Map Building System

Figure 2 shows the architecture of our system. In this figure, we omit other modules such as the path planner, navigator, pilot, and supervisor (see [8]) in order to concentrate on the map building system.

The 3-D world model for a mobile robot consists of three kinds of maps: a sensor map, a local map, and a global map. Elfes [15] in his sonar mapping and navigation system proposed multiple axes of representation of a sensor map (resolution axis, geographical axis, and abstraction axis) and adopted three levels (view, local map, global map) on the geographical axis. We generalized these three levels so that other sensory data are applicable. Figure 3 shows the geometrical relation between the coordinate systems of the sensor map, the local map, and the global map. Each sensor has its own coordinate system; for example, an intensity image is represented in the camera centered coordinate system and a range image in the range finder centered coordinate system, both of which are fixed to the robot (vehicle). Here, we assume that the relation between sensor coordinate systems and vehicle coordinate system is known, and that motion information (the relation between local maps at different locations) is available, but not always accurate. A Local Map Builder builds the local maps which represent an integration of the sensor maps in the robot (vehicle) centered

coordinate system. Stereo matching, which we do not consider in this paper, is one possible strategy of local map building for obtaining the depth map (local map) [16,30]. Here, we propose height maps obtained from the range image as local maps. The height map is analyzed by the Obstacle Finder and the Obstacle Classifier to segment it into unexplored, occluded, traversable, and obstacle regions and then to classify the obstacle regions into artificial or natural objects. The result of the height map analysis is mapped onto the intensity image by the Obstacle Mapper in order to segment the intensity image. The global map is a final map obtained by the Local Map Integrator which matches and updates local maps at different observing stations in the world coordinate system.

In the following, each module is described along with some experimental results.

3. HEIGHT MAP ANALYSIS

3.1 Local Map Builder (From Range Image to Height Map)

The local map builder builds local maps from sensor maps. Here, we deal with a video image taken by a single camera and a range image obtained from our range finder [23] as sensor maps. Figures 4 (a) and (b) show examples of these sensor maps. The input scene includes a straight road, T-type intersection, two cabins, one truck, two cars, a mailbox, a stop sign at the intersection, trees, and bushes as shown in Figure 4(a). Figure 4(b) is the range image corresponding to Figure 4(a). The darker points are closer to the range finder and the brighter points are farther from it. In the white regions, range information is not avail-

able due to inadequate reflection or occlusion. Although actual range finders such as the ERIM range scanner [19] measure radial distances rather than Cartesian coordinates along both axes, the range image obtained from our range finder has irregular coordinate axes due to its special ranging geometry [23]; the vertical coordinate is radial but the horizontal coordinate is the same as that of the intensity image.

The range image is transformed into a height map in the vehicle centered coordinate system based on the known height and tilt of the range finder relative to the vehicle. The height map is a 256×256 image; each pixel corresponds to 1 mm^2 on the board. The entire map corresponds to a square of side length 256 mm; the scale of the board is 87:1 (HO scale). Gray levels encode height from the assumed ground plane. Since the range is sparse and noisy at distant points, smoothing is necessary. We applied an edge-preserving smoothing method [25] to the height map in order to avoid a mixed pixel problem of high and low points. Figure 5 shows the filtered height map of the input scene (Figure 4(b)); Figure 5(a) shows a gray level image and Figure 5(b) shows its perspective view.

One drawback of the height map is that it is unable to represent vertical planes, especially these under horizontal or sloped planes, because the range information corresponding to multiple points in the vertical direction is reduced to one point in the height map. This is especially undesirable since the range information on the vertical planes is more accurate than that on the horizontal planes. Thus, we compute a multiple height map for each image which includes the maximum and minimum heights for each point on the height map, and the

number of points in the range image which are mapped into any point on the height map. In Figure 5(a), the maximum height for each point is shown. Figure 5 (c) shows the differences between the maximum and minimum heights. High difference regions are candidates for vertical planes. Counting the number of points inside such candidate regions can be used to check for the existence of vertical planes.

3.2 Obstacle Finder (Segmentation of Height Map)

The first step in the height map analysis is to segment the height map into unexplored, occluded, traversable, and obstacle regions. The height map consists of two types of regions—those in which the height information is available and those in which it is not. The latter regions are classified into unexplored or occluded regions. Unexplored regions are outside the visual field of the range finder, and therefore are easily detected by using the calibration parameters of the range finder (height, tilt, and scanning angle). The remaining regions in this category are labeled as occluded regions. Some regions which are not occluded may be classified into occluded regions if the height information is unavailable due to causes such as inadequate reflection. These regions can be often seen inside bushes or trees with many leaves.

Finding traversable regions is straightforward. First, identify those points close to the assumed ground plane and construct atomic regions for the traversable region. Next, expand the atomic regions by merging other points surrounding them which have low slope and low curvature. The desirable feature of the height map is that the outputs of the first and second derivatives of the height

map correspond to the magnitudes of the slope and curvature of the surface because the locations of the points in the height map are represented with Cartesian coordinates. Figures 6 show the magnitudes of the first (Sobel) and second derivatives of the height map (Figure 5(a)) using a mask size of 3 by 3 pixels. The remaining regions are labeled as obstacle regions. Figure 7 shows the final result of the segmentation of the height map. White, light gray, dark gray, and black regions are unexplored, occluded, traversable, and obstacle regions, respectively. We can see that the boundaries of the obstacle regions have high slope and/or high curvature (see Figures 6).

The result of segmentation of the height map should be useful for path planning since many path planning algorithms are based on a top view of the configuration of obstacles and free space [26].

3.3 Obstacle Classifier

The segmented height map constructed by the Obstacle Finder is very useful for navigation tasks such as avoiding obstacles, but does not contain sufficient information explicit enough for higher level tasks such as landmark or object recognition. As a first step in object recognition, we try to classify obstacle regions as artificial objects or parts of natural objects. Many artificial objects such as cabins, cars, mailboxes, and road signs (shown in Figure 4(a)) have planar surfaces, which yield constant slopes and low curvatures in the height map and linear features in the intensity image. On the other hand, natural objects such as trees and bushes have fine structures with convex and concave surfaces, which yield various slopes and/or high curvatures in the height map and therefore large

variances of brightness in the intensity image (the reverse is not always true).

Thus, utilization not only of the height map but also of the intensity image is useful for obstacle classification. In order to use the brightness information in the intensity image, we map the obstacle regions into the intensity image to segment it. The mapping of obstacles into the intensity image at first seems straightforward based on the geometrical relation between the camera and the range finder. However, it is complicated by the need to correctly choose between the maximum and minimum heights associated with each point in the height map. We should use the minimum height when the obstacle is bounded by traversable regions and the maximum height when the obstacle occludes other objects behind it. Classifying the boundaries of obstacle regions in the height map and using the multiple height map, the obstacle mapper maps the obstacles into the intensity image as follows.

(1) Classify each boundary point of the obstacle region in the height map according to the geometrical relation between the point, the occluded region and the traversable region in the segmented height map (Figure 7).

(2) Use the minimum height if the point is adjacent to a traversable region or is on an occluded boundary (a boundary point is labeled as on an occluded boundary when the occluded region is between the boundary point and the range finder).

(3) Use the maximum height if the point is on an occluding boundary (a boundary point is labeled as on an occluding boundary when it is between the occluded region and the range finder).

Figure 8 shows the result of this mapping. The cars on the road and in front of the cabin on the right side, the mailbox and the bushes on the left side are finely segmented in the intensity image. The truck at the intersection is mapped incorrectly because its range image contains only a vertical surface whose boundary shape is very unstable. The bottom roof line of the cabin on the left side is also incorrect because of the bad range data. The reason that the top roof line of the cabin on the right side drops suddenly to the ground plane is that there is a lower object behind the cabin and the obstacle region in the height map includes both the cabin and the lower object.

The next step is to classify the obstacles using the properties of the height map and the brightness in the intensity image. Before identifying each obstacle region as an artificial or natural object, resegmentation is necessary because some regions include both artificial and natural objects, for example regions A, B, and C in Figure 8(b). Region A includes a cabin and bushes beside it, region B includes a cabin and a lower object behind it, and region C includes a stop sign and bushes. There must be boundaries between two different regions inside one obstacle region in the segmented height map and these boundary points must have high slope and/or high curvature. Figure 9 shows the result of resegmentation using the high slope and high curvature points. There are new interior boundaries in the obstacle regions A, B, and C. Next, the obstacle classifier classifies each resegmented region according to the following criteria.

(1) If a region has sufficient size (larger than a pre-determined threshold), constant slope (small variance of slope), and low curvature (low mean curvature and

small variance of the curvature), then the region is an artificial object.

(2) If a region has sufficient size and high curvature (high mean curvature and large variance of the curvature) and large variance of the brightness in the intensity image, then the region is a part of a natural object.

(3) Otherwise, the region is regarded as uncertain in the current system.

In Figure 9, white, gray, and black regions correspond to artificial, natural, and uncertain objects, respectively. Small regions are almost always labeled as uncertain. The roofs of the two cabins and the car on the road are correctly interpreted as artificial objects. However, the truck, the mailbox, and the stop sign are misinterpreted as natural objects because of high curvature due to vertical planes. The car in front of the right cabin is also misinterpreted as a natural object because the range data from the front windshield is very noisy and yields spurious high curvatures. Uncertain regions and some regions with vertical surfaces require closer examination for correct interpretation.

3.4 Local Map Integrator

During the motion of the vehicle, the system produces a sequence of local maps constructed at different observation stations. These local maps should be integrated into a global map in the world centered coordinate system. The local map integrator consists of two parts; the first one matches two local maps to determine the correct motion parameters of the vehicle, and the second updates the descriptions of region properties. Matching is performed as follows by using the two segmented height maps at different locations.

(1) Match the traversable regions between the two height maps. Since the

traversable regions are usually the larger planar regions in the segmented map and rough estimates of the motion parameters are ordinarily available from the internal sensors of the vehicle, this matching is relatively straightforward. From this matching, the number of motion parameters of the vehicle is reduced from 6 to 3; two translational components and one rotational component on a plane.

(2) Determine the remaining motion parameters by matching the vertical plane parts between the two segmented height maps. To do this, the vertical planes in the height map should be correctly identified by the obstacle classifier as described in the previous section. The vertical planes are represented as line segments in the height map. The end points of these line segments are used for matching, but the end points bounded by occluded regions are not used for matching because the locations of these points might change. Also, special care needs to be taken for moving objects. In the current system, we use a heuristic for detecting moving objects. An obstacle surrounded by traversable regions is a candidate moving object because moving objects should be inside traversable regions (except for flying objects). The vertical planes belonging to the candidate moving objects or bounded by them are not used for determining the motion parameters.

From the motion parameters determined in this way from two segmented height maps, the local map integrator overlays the two maps in the world centered coordinate system in order to update region properties. Labels of regions (unexplored, occluded, traversable, and obstacle) can be transferred from the first map to the second map as shown in Figure 10. The local map integrator adopts

a label oriented by an arrow when a region has different labels in the first map and the second map. Special care needs to be taken for moving objects because their labels might change from "obstacle" to "traversable" between the two maps (see the broken arrow in Figure 10). Currently, we are developing the local map integrator, and no experimental results are available.

4. DISCUSSION AND FUTURE WORK

A map building system for a mobile robot that uses sensory data has been described. We have proposed the use of a height map obtained from a range image to support various tasks such as path planning and landmark recognition. The height map is easy to recover and calculation of geometrical properties such as slope and curvature is straightforward.

The current obstacle classifier primarily uses height information and makes little use of brightness information in identifying obstacles as artificial or natural objects. The experimental results include some errors. Errors due to vertical planes can be corrected verifying the existence of the vertical plane in the multiple height maps and obtaining more correct parameters from the range image (sensor map). Other errors might be corrected by the use of color images since color information is often useful for segmentation of images of outdoor scenes [27].

The global map is obtained in the current system from geometrical matching of the height map and simple manipulation of the labels (unexplored, occluded, traversable, and obstacle) and sublabels (artificial or natural). For more compli-

cated scenes or tasks, more complex representations would be necessary. The ultimate goal of our research is to make our map building system useful in the context of knowledge based systems such as [28,29] in which the manager provides the means for integration of sensor-based data with stored knowledge to construct a world model.

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Figure 1. Photo of new terrain board.

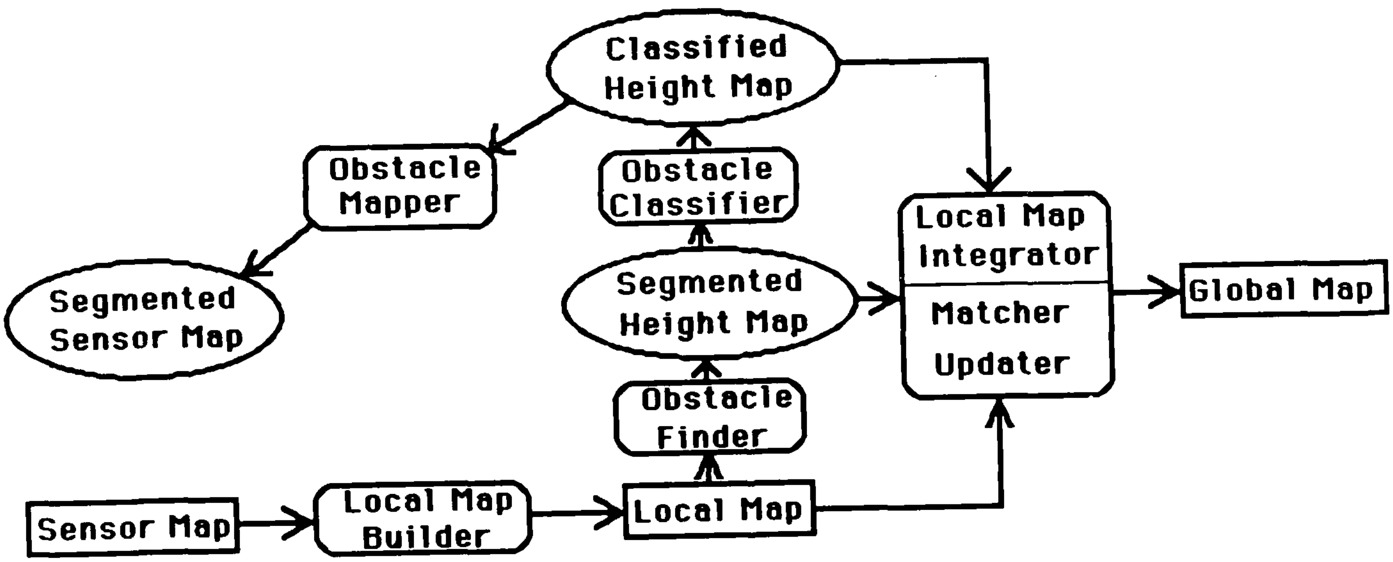

Figure 2. Overview of map building system.

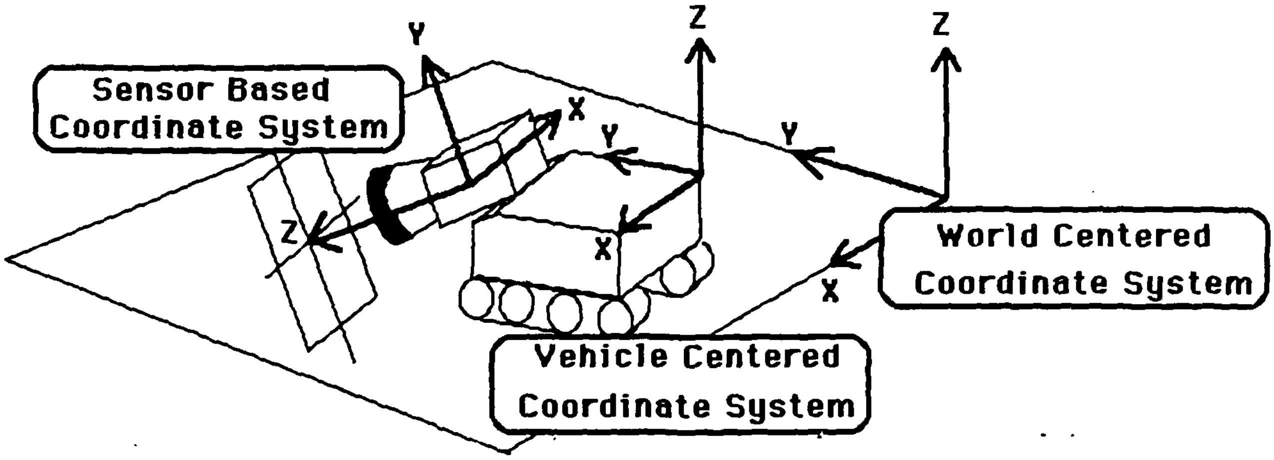

Figure 3. Geometrical relation of the coordinate systems of the three maps.

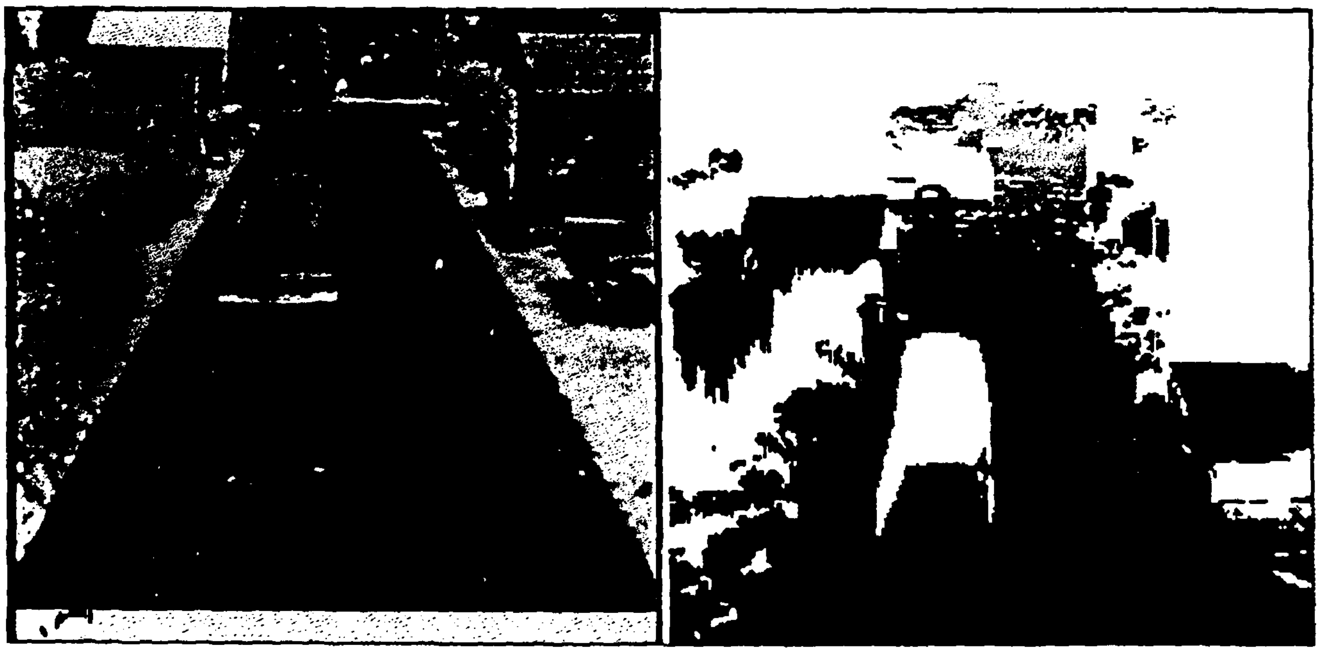

Figure 4. Sensor maps. (a) An intensity image viewed from the camera; (b) a range image viewed from the range finder.

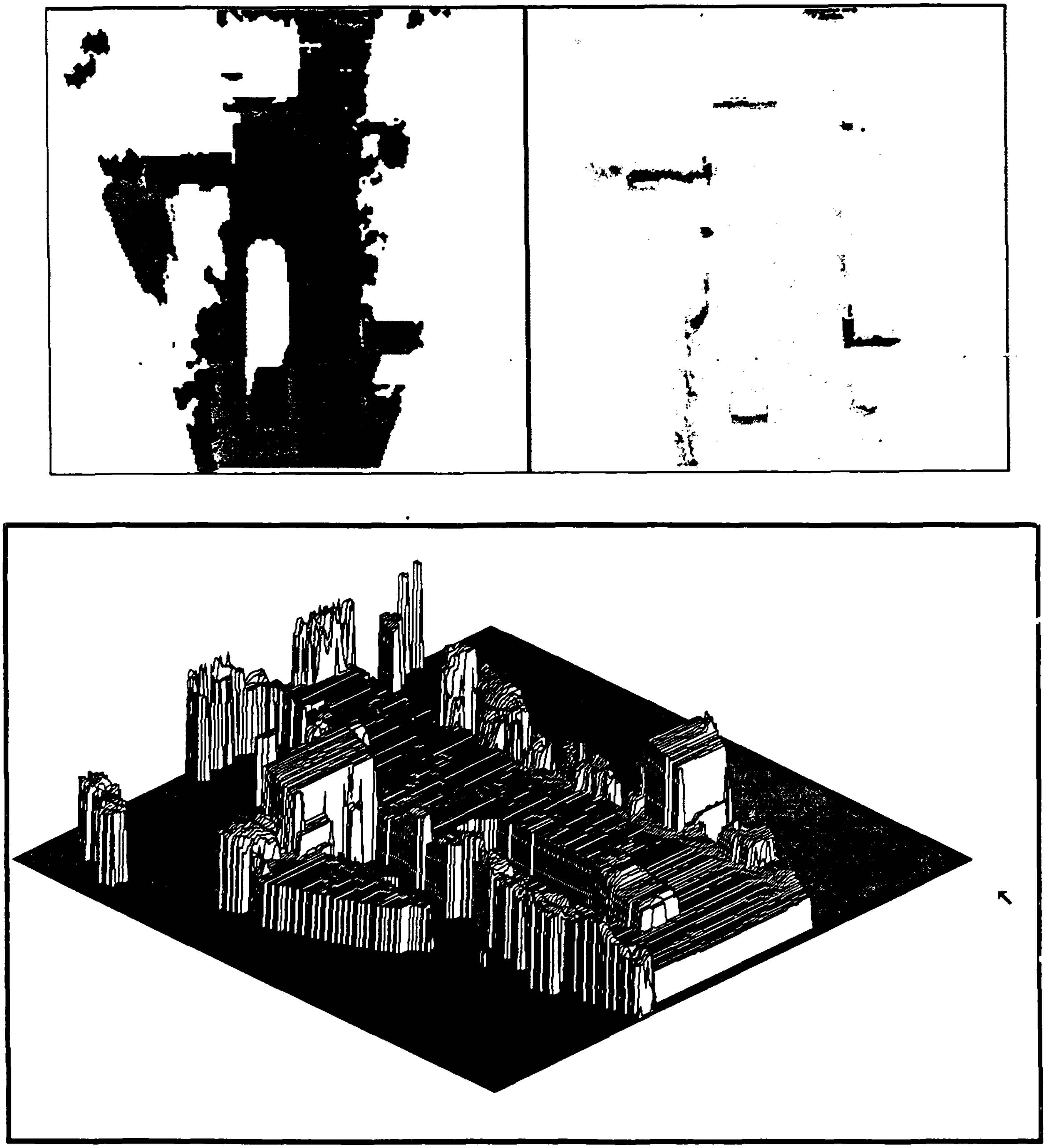

Figure 5. Height map. (a) A gray image; (b) its perspective view; and (c) difference image between the maximum and minimum heights.

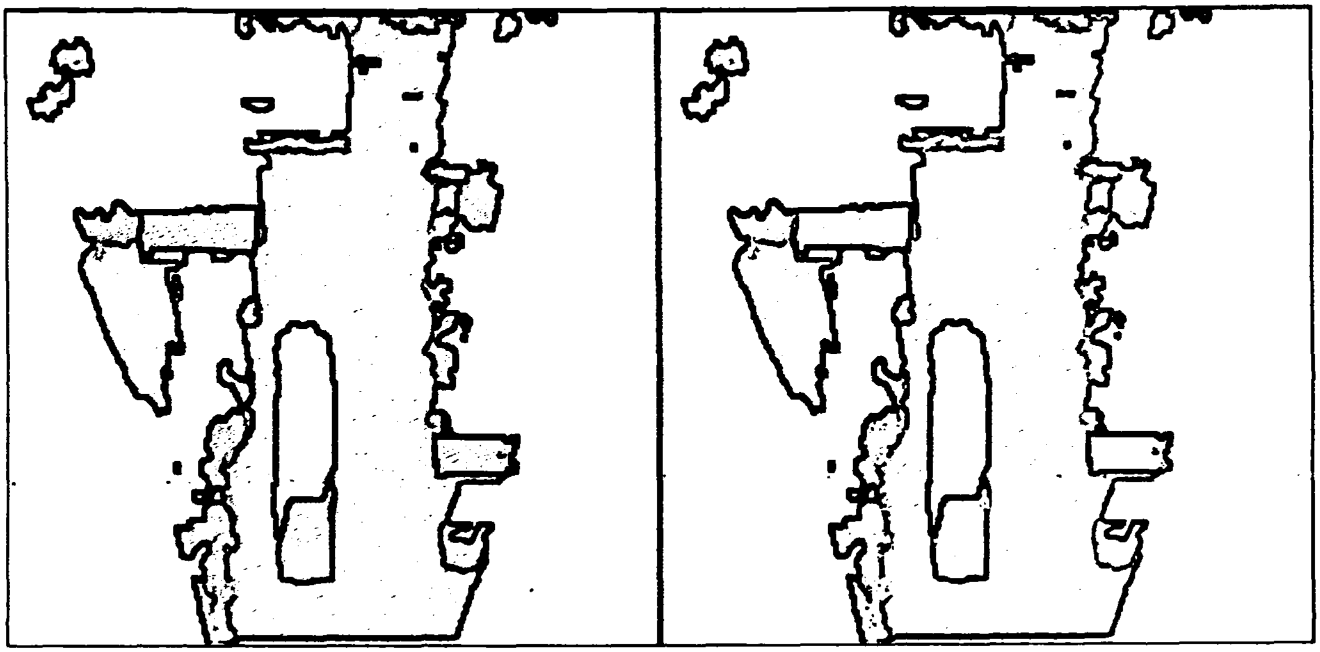

Figure 6. Slope and curvature maps. (a) Slope; (b) curvature.

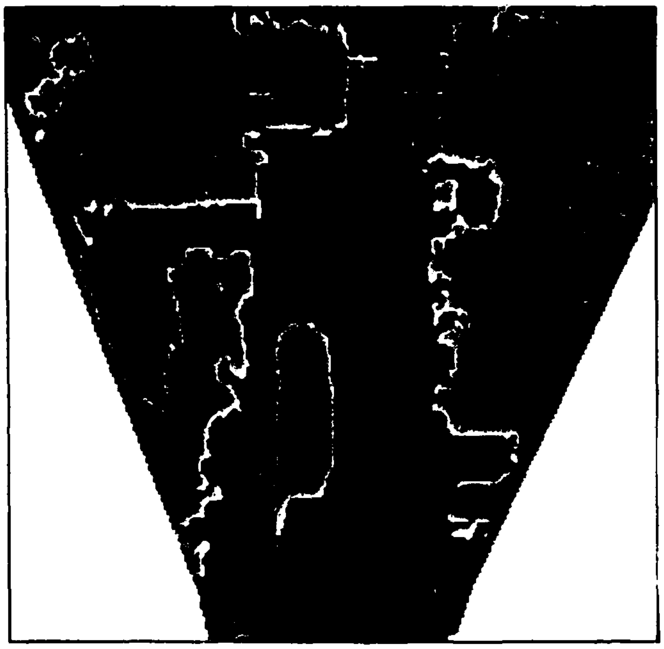

Figure 7. Segmentation of height map.

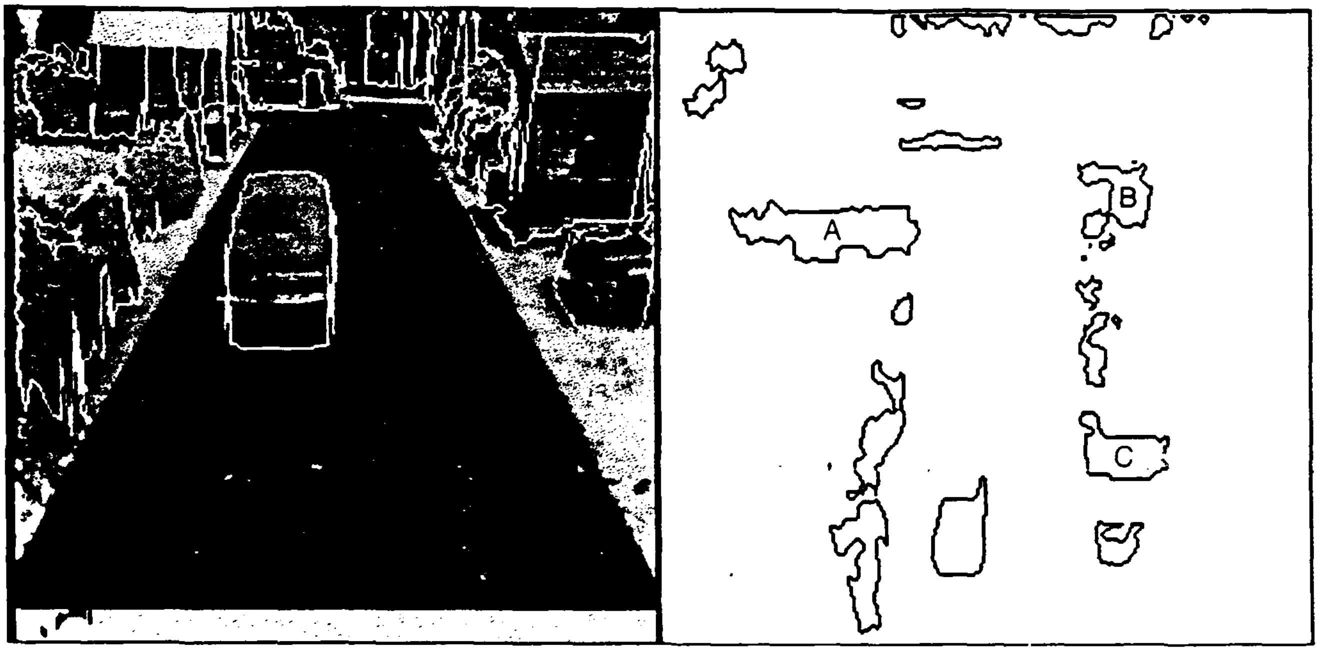

Figure 8. Mapping an obstacle region into the intensity image. (a) Mapped region; (b) obstacle map.

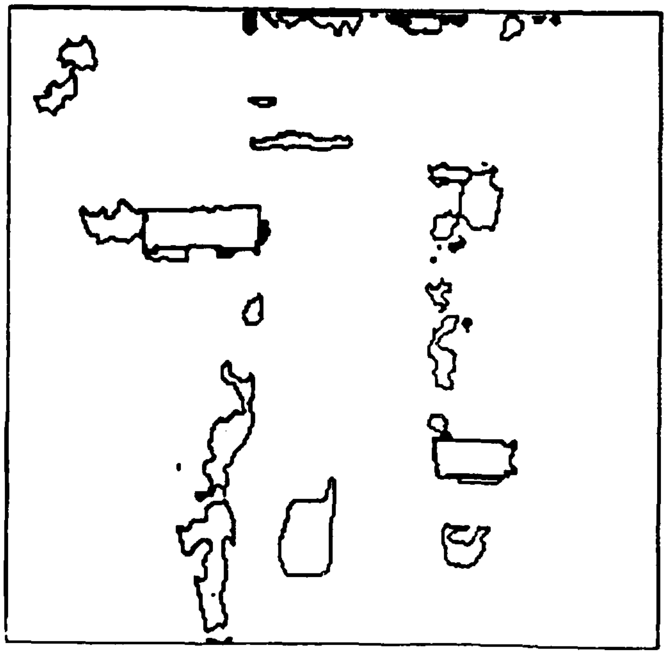

Figure 9. Classification of obstacles.

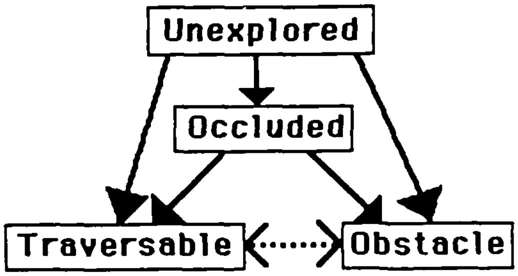

Figure 10. Transition of labels.

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